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Article

Insight into Predicted Shocks in Tourism: Review of an Ex-Ante Forecasting

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Abstract: The purpose of this paper is to provide an insight into the modelling and forecasting of unknown events or shocks that can affect international tourist arrivals. Time-dependence is vital for summarising scattered findings. The usefulness of econometric forecasting has been recently confirmed by the pandemic and other events that have affected the world economy and, consequently, the tourism sector. In the study, a single Slovenian dataset is input for the analysis of tourist arrivals. Vector autoregressive modelling is used in the modelling process. The data vector from the premium research is extended up to 2022. The latter is an ex-post empirical study to show the validity of the ex-ante predictions. This paper analyses the synthesis of ex-ante predictions which fill the gap in the ex-ante forecasting literature. The study of previous events is relevant for research, policy and practice, with various implications.

Keywords: calamitous events; econometrics; forecasting; pandemic; shocks; time-series; tourism



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1. Introduction

After a decade of positive economic growth and years of adverse pandemic events, tourism is still a crucial economic part of the global and national economies. Additionally, scholars are developing tourism demand and supply research issues even more broadly and deeply, while tourism suffers the most when outliers reach specific countries or continents (Estiri et al. 2022). Due to this, the present research:

1. introduces a technical review and some steps for tourism modelling,
2. validates the need to encourage scholars of technical steps to predict ex-ante and exogenous event in tourism,
3. discusses modelling and forecasting if tourism's key determinants, which are crucial in modern economies.

The tourism industry is highly volatile due to seasonality and other determinants. Seasonality has been widely researched, but calamitous events and their impact on the tourism sector are still underestimated.

Only a few researchers have warned the tourism industry of a possible forthcoming event (Gricar et al. 2022) before it happened. Moreover, new volatilities, inflation, interest rates, war, environmental disasters, catastrophic summer flights and high-energy prices represent recent stochastic events that affected tourism demand. Therefore, the motivation of this study is to highlight some significant ex-ante results that have been published in a previous study (Gricar et al. 2022). Nevertheless, a detailed literature review of the newest articles published using quantitative data and econometric methods on recent shocks (Allen 2022; Herby 2021; Xavier 2021) is the first objective of the research. The study's second specific objective incorporates several directions of shocks concerning tourism demand.

The most influential idea is that shocks negatively affect tourism demand in the medium to long term. The third specific objective provides one reliable modelling structure using time series data in tourism to improve the prediction power of the model.

The study aims to motivate researchers to express their results more frequently and quickly. Time-series modelling and forecasting are among the most efficient tools for analysing tourism demand. As [Ntounis et al. \(2022\)](#) stated, predictions are only possible with time-series data and the tourism and hospitality industry lacks credible predictions. Therefore, this study aims to develop predictions for tourism using state-of-the-art econometric methods and models. Modelling is an essential technical issue important for quantitative research in the tourism industry, tourism economics and tourism management. There are three objectives:

1. a literature review of ex-ante studies to find the existence of ex-ante predictions of a pandemic,
2. in the tourism industry, time-series econometrics could be used to predict fluctuations in demand for certain shocks. This method would also be useful in technical analysis, a step-by-step approach that helps predict future trends,
3. modelling ex-ante forecasting for tourism is an essential field in science, therefore we present an empirical example here.

The study is structured as follows. The following section explores the literature regarding the impact of shocks on the tourism market. The next part explains the tools and techniques used. The fourth part of the paper provides a testing ex-ante forecasting model for tourism. The last two sections discuss the results, findings and conclusions.

2. Literature Review

The literature review is based on a review of studies published in scientific journals cited in the Scopus database. The literature review is based on two recently published papers. The first is on pandemics by [Morse et al. \(2012\)](#). The second is on tourism demand under pandemics by [Kuo et al. \(2008\)](#). Both studies warned that pandemics and epidemics are closer than tourism management and policymakers think. Both studies recommended a need to predict future events with reliable modelling, whereas [Kuo et al. \(2008\)](#) gave an example using the Autoregressive Moving Average Model (ARMA), where tourism demand is a proxy of international tourist arrivals and the regressors were two different viruses.

Before applying the data and the methodology, a comprehensive literature review is presented to confirm the gap in the literature. In economics and tourism, there is an essential need to predict future events and shocks quickly and efficiently without losing critical information hidden in the data.

A pioneering paper detected an urgent need for modelling the pandemic at a pre-emptive (ex-ante) stage ([Morse et al. 2012](#)). They pointed out that no pandemic has been predicted before infecting human beings. As a striking point, between 2020 and mid-2022, [NIH \(2022b\)](#) gives evidence that 358,355 pieces of research were included in PubMed to back-predict (ex-post) pandemic in the case of the coronavirus COVID-19 outbreak. On the other hand, only 65,777 ([NIH 2022a](#)) papers were published before 2020 (1900–2019) when the keyword “pandemic” was researched. The publisher notes: “Filters activated: Publication date from 1 January 1900 to 31 December 2019. Clear all to show 345,304 items” The latter is for mid-2022. The difference shows that from 2020 to mid-2022 ex-post 279,527 articles were published.

Therefore, few studies have recognised the new pandemic threat at a pre-emptive phase ([Gricar et al. 2022](#)). Most articles investigated the recent outbreak and its medical, sociological and economic consequences, but do not provide forecasts before the outbreak occurs. The present study considers this gap in the literature to improve forecasting and prediction that can help policymakers to prevent damage to human health, lives and travelling. To support this statement, we have checked the paper’s citations by [Kuo et al. \(2008\)](#). The Scopus database stored eight citations in 2009 for this research, where the

authors insist that further investigation is fundamental to predicting the next pandemic and preventing crises in the tourism industry. Pre-pandemic citations (written in parentheses) are: 2010 (5), 2011 (1), 2012 (4), 2013 (7), 2014 (6), 2015 (7), 2016 (6), 2017 (7), 2018 (7), and 2019 (6). Based on 11 years, the average annual citation is 5.82. After COVID-19, the average annual citation increased to 73.2 citations in 2020–mid-2022. The data from the Scopus database is as follows: 2020 (30), 2021 (91) and half of the year 2022 (62) (Scopus 2022).

We utilise the back-predict (ex-post) and pre-emptive (ex-ante) (Figure 1) by Morse et al. (2012). A pre-emptive step could be to prevent the spread of the initial emergence of pandemics: “to predict pandemics”, but the focus of studies after 2020 is two-fold. First, is to back-predict an event accurately using mathematics and a sophisticated array of computable models. Second are design models for tourism to accurately predict future pandemic spread. Based on the literature review and according to the aim, this research approaches tourism demand prediction of events forecast by the Vector Autoregressive Model (VAR) and cointegrated (C)VAR modelling based on tourist arrivals data as a regressed variable. Therefore, in this study, the modelling process is based on tourist arrivals and viruses as primary variables using a data sample from Slovenia. The extended modelling method is a VAR.

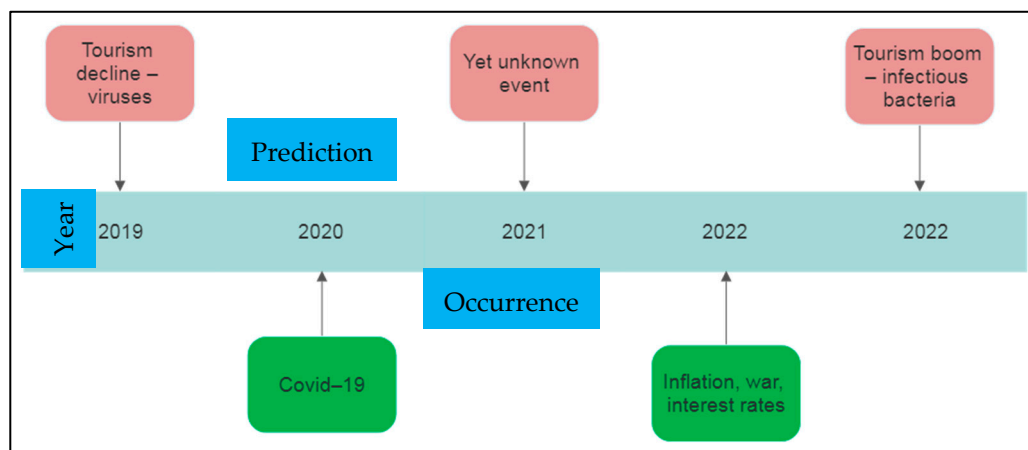


Figure 1. A timeline of pre-emptive approach (red) and shock response (green). Source: Compiled by authors based on Gricar et al. (2022).

Differential variables can cause developments in tourism. Page (2009) discussed that every tourist is a potential patient. Therefore, it is essential to regulate and analyse the health status of potential and effective tourists in the destinations. The novelties of this study are: (i) valid ex-ante forecasting using time series, and (ii) attested variable choice. Strategic and risk planning, therefore, could be based on time series econometrics and on ex-ante tourism forecasting assessment (Liu et al. 2022a; Srakar and Vecco 2017).

2.1. Literature Forecasting 2020 Pandemic: Pre-Emptive (Ex-Ante) Research Review

Grand (2016) stated that the biggest challenge to the tourism industry would be the treatment of viruses. Smith et al. (2019) defined the economic loss caused by public health and travel. Before these two dates (e.g., 2016 and 2019), Page (2009) stated that tourism should be studied in an interdisciplinary manner (tourism, public health and econometrics).

Additionally, (ii) Kuo et al. (2008) and McAleer et al. (2010) analysed the tourism industry affected by two groups of viruses; (iii) Morse et al. (2012) reported that air travel causes the possibility of high spread of microbes; (iv) Gössling (2002) exposed the threat of dispersion of diseases; (v) Shi and Li (2017) proposed validated modelling for unexpected events in inbound tourism; (vi) Jonung and Roeger (2006) and Chung (2015) researched the macroeconomic losses and airport minuses caused by pandemics; and (vii) Petty (1989) diagnosed that long-haul travel causes the possibility of an explosion of bacteria and viruses among travellers.

These few authors directly warned about the imminent outbreak beforehand. A detailed analysis with a precisely defined prediction as a pre-emptive warning of new virus shock for tourism was presented in 2019 (Gricar et al. 2022). Therefore, the year 2019 is taken as a time limit in the present study, while trying to demonstrate how crucial accurate forecasting of unexpected events is.

2.1.1. The Year 2009

Smeral (2009) discusses scenarios for analysing and forecasting demand for international travel in 15 EU countries during the economic crisis. Brida and Risso (2009) discuss the tourism demand in South Tyrol, mostly travel costs and proxy prices. Kuo et al. (2009a) discuss the dimensions of the SARS pandemic and forecast the cases that might affect humans. Ertuna and Ilhan Ertuna (2009) researched the effects of new shocks on tourism demand. Kuo et al. (2009b) researched the main determinants that contributed to tourist arrivals demand, while Yuan and Wang (2009) forecast tourist arrivals demand for the upcoming year.

The review of studies published in 2009 showed that not all are based on forecasting. A similar study was conducted by Li (2009), where 180 articles were studied on forecasting and demand in the case of Greater China.

2.1.2. The Years from 2010 Up to 2019

Jayaraman et al. (2010) estimated the number of tourist arrivals in Malaysia. Song and Lin (2010) forecast the tourism demand for outbound and incoming tourists in Asia after the economic crisis. McAleer et al. (2010) discussed tourist arrivals and the impact of viruses.

Song et al. (2011) forecast the impact of economic crises on hotel room demand in Hong Kong. Ghaderi et al. (2012), implementing qualitative research, clearly stated that events change strategic orientation in tourism management. Cahyanto et al. (2016) added the idea of preventing forthcoming pandemics by analysing Ebola in the United States (US).

Nor et al. (2016) highlighted the importance of valid forecasting for tourism management and the choice of variables to assess accurate data isolation on time series. Cró and Martins (2017) highlighted for the first time in the tourism literature the problem of ex-post identification of shocks causing tourism. Rosselló et al. (2017) warned about the additional possibilities of health problems caused by tourism. Additionally, they recognised quantification of health policies, which should be taken into consideration in future international health assessment programmes. Shi and Li (2017) and Gozgor and Ongan (2017) defined shock as an unexpected event and defined ex-post time series modelling on causation of breaks.

Moreover, similar studies in ex-post research studying shocks (economic crises, Swine flu, etc.) to predict tourism demand with a tourist arrivals time series variable have been investigated by several scholars such as Haque and Haque (2018), Novelli et al. (2018), Su and Lin (2019), and Puah et al. (2019).

As can be seen, there is a significant gap in identifying a forthcoming break in the scientific literature (Cró and Martins 2017). The results of detailed desk research of more than a hundred empirical studies confirmed that few researchers have predicted a shock on a pre-emptive (ex-ante) occasion. Moreover, research with crisis content, i.e., on shocks, is more frequently published after the fact occurs than immediately before.

2.2. Literature Analysing 2020 Pandemic: Back-Predict (Ex-Post) Research Review

With the COVID-19 shock, the number of studies has increased substantially (Wut et al. 2021). Shaukat et al. (2020) analysed the review of published ex-post studies on COVID-19 and SARS. Chen et al. (2020) recognised the impact of a pandemic on several tourism sub-sectors. Nevertheless, there are another 26 studies which have analysed recent pandemics and tourism. The most frequently cited study is by Guan et al. (2020) (258 citations in

Scopus), whereas the most cited study in the year 2021 is [Wen et al. \(2021\)](#) (260 citations in Scopus), and in 2022 [Toanoglou et al. \(2022\)](#) (18 citations in Scopus) on a half-a-year 2022 basis.

Critically reviewing the previous research, one can notice that the vast majority of studies are ex-post studies, so most scholars deal with time series methodology and empirics after the event. Overall, highlighting the exposure of this study can be summarized as:

- closing the gap in the forecasting literature by adding accurate ex-ante predictions and forecasting using time series econometrics.

3. Methods

It is crucial to discuss the events in tourism as external factors (Figure 1). The supportive literature is presented in Table 1 and additional comments are shown in the following subsections.

Table 1. The review of forecasting.

Ex-Ante Prediction, Modelling	Pictogram
Viruses, OLS	Figure 2
Viruses, ARIMA	Figure 2
Viruses and unknown events, CVAR	Figure 3
Microbes, Panel	

Event	Forecasted on	Event occurred	Dimension	Source
Viruses	14. 11. 2019	March 2020	77%	Conference proceedings




Figure 2. Ex-ante research on predicted “viruses”. Source: [Gricar et al. \(2022\)](#).

Event	Forecasted on	Event occurred	Dimension	Sources
Viruses	8. 8. 2021	End of 2021	18%	Scientific article
Unknown event	27. 8. 2021	Autmn 2021	82%	Article in a daily newspaper

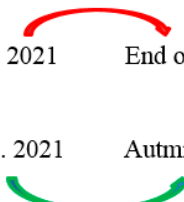


Figure 3. Ex-ante research on predicted “tsunami” at the end of February 2022. Sources: [Gricar et al. \(2022\)](#).

Figure 1 explicitly depicts how the predicted events occur using time series econometrics, reliable models and intuition regarding the choice of the variables and accompanied methodology.

3.1. Hypotheses Development

The hypotheses development is based on the previous literature concerning the most recent events that have caused shocks to the tourism economy.

3.1.1. The Pandemic

Using intuition, authors [Gricar et al. \(2022\)](#) have predicted specific problems in the ex-ante tourism demand by researching data from Slovenia and Croatia. The time series method was used in all presented papers in Table 1. These two countries are European tourist destinations where tourism plays a vital part in the national economy, especially in Croatia, where it forms about 20% of gross domestic product. Therefore, the determinant of tourist arrivals could consequently be one of the best variables for predicting future events,

while known presently in time series econometrics defined from past phenomenon (Gricar et al. 2022).

The methods used in the studies presented in Table 1 were a CVAR, an autoregressive integrated moving average model, and a simple ordinary least squares regression (OLS). All calculations were based on secondary data. The data were collected from imminent sources such as statistical offices and other institutions that collect data randomly (Gricar et al. 2022).

There is little ex-ante research (Figure 1) about recent events or stochastic shocks, as presented by Gricar et al. (2022). Tourist arrivals in Figure 2 clearly illustrate an obvious shock at the beginning of 2020. That shock was predicted just before, e.g., in November 2019.

On the other hand, many researchers speak of a new normal (Guo et al. 2022; Junfeng et al. 2022; Liu et al. 2022b). However, it is already known that there is no unique standard, but rather new dimensions like the green economic recovery defined by Liu et al. (2022b). On the other hand, minimalism, self-sufficiency, and micro-mobility, among others, are rising instead of cars and flights (#shame) or Airbnb (Price et al. 2022). The latter do not have sufficient public control over pollution, costs and taxes and, therefore, could be transformed by emerging solutions such as green hotels with rainwater, self-generated energy, car-free travel and flights based on short trips.

Policymakers have taken tourism out of action during a pandemic, and to avoid future distractions from such decisions and, consequently, future events, they need to consider CO₂ emissions in advance (Gricar et al. 2022). Gricar et al. (2022) noted that tourism demand would increase this decade if policymakers consider sustainable factors (Estiri et al. 2022). Until then, tourism will suffer from low or dynamic and volatile (not just seasonal) demand, as was the case from 15 July 2021 until the “tsunami” of events hit in late 2021/beginning of 2022 (Gricar et al. 2022).

3.1.2. Additional Events

Gricar et al. (2022) warned about unusual circumstances predicted using modern econometric methods on time series (Figure 3). The prediction statement can be seen from Figure 3—that an unexpected event could happen at the end of the year 2021, using two critical variables that threaten tourism demand, CO₂ and tourist arrivals. It should also be noted that tourism is a worldwide industry. Incoming tourists are the most influential paradigm for econometric models and forecasting. The notion was that the unknown event should occur at the end of 2021, but this was prolonged to February 2022. Due to the previous empirical literature, this is not such an unexpected issue (Åtland 2020). Some newspapers highlighted that this is due to the Winter Olympic Games (The New York Times 2022). The daily news could also be a further investigation hypothesis (Koonin 2022; Koval et al. 2022; Oleksiyenko et al. 2021). Overall, this study wants to highlight that tourism demand could, alongside CO₂ emissions, forecast unusual events when demand and CO₂ are falling rapidly. The econometrics in time series did such research (Farooq et al. 2022).

Additionally, as seen in Figure 2, the prediction of Gricar et al. (2022) states that the recent pandemic (e.g., Autumn 2021) will cause a decline in 18% of tourism demand, the rest still being unknown parameters at the time of the initial study (May 2021) (Figure 2). Other possible factors occurring in tourism demand by early 2022 are high energy prices or low energy supply, inflation and natural disasters, which are visible now (Liu et al. 2022b). Which of all these determinants could be the leading “disaster” effect in a call for subsequent research?

3.1.3. Tourism Boom and Hypothesis Development

It is worth adding that the prediction of an earlier study by Gricar et al. (2022) found that the next tourism boom could be based on bacterial infections, while the results confirmed that any infection could lead to higher international tourist arrivals. Before

proceeding to the hypothesis, the predictions made by the European parliamentary research service are noted (EPRS). Looking ahead, recovery is expected to be uneven across sectors, with some recovering relatively quickly and others dying out in the coming years. For example, tourism is expected to return to 2019 levels between 2022 (domestic travel) and 2024 (international travel), while retail is expected to take about five years to recover. [Gricar et al. \(2022\)](#), expected similar findings. Therefore, well-designed policies can mitigate the effects of the crisis. In the EU, the immediate “rescue” policy to deal with the pandemic included measures to maintain the level of domestic tourists, effective in dealing with transitory and asymmetric shocks. In its fall 2021 economic forecast of EPRS, the European Commission expects the EU economy to return to pre-pandemic output levels in the third quarter of 2021 and move from recovery to growth, although growth rates will continue to vary across the EU.

In conclusion, based on the literature review, the hypothesis is: The next tourism boom in Slovenia (positive development of tourist arrivals) will be influenced by increased bacterial infections. These infections are generated primarily by microbes.

3.2. Methods

Prediction using time series models is crucial. Several studies deal with different variables ([Ahumada and Cornejo 2021](#); [Katircioglu et al. 2018](#)), but no study deals with tourist arrivals and microbes in the context of $I(1)$ cointegration.

[Juselius \(2009\)](#) and [Escribano et al. \(2021\)](#) recognised some relationships between aggregate secondary variables and the importance of a data vector of the chosen order of integration $I(d)$.

The data vector V is intuitively and strategically designed for reliable modelling and is usually named concerning the research question or hypothesis; thus, its econometric application is as:

$$V = \mathbb{R}^n \begin{bmatrix} i \\ x_{p,j} \\ \Delta \\ t \end{bmatrix}_T^{I(d)}, \quad T = 1, 2, \dots, t, \tag{1}$$

where i is a panel information (e.g., country), p is a number of j parameters (e.g., time series variables), $I(d)$ is the order of integration, Δ is a data vector treatment such as dummies and logarithms, n is the number of scalars and T is the length of the time series t . The definition of a data vector allows scientists to define the measurement of misspecification, which is a standard procedure.

Nevertheless, the general model used in this research is a dynamic autoregressive model (AR) ($\rho = 1$) with a constant term:

$$y_t = \rho \cdot y_{t-1} + \gamma \cdot (1 - \rho) \cdot t + \rho \cdot \gamma + (1 - \rho) \cdot y_0 + \varepsilon_t, \text{ and} \tag{2}$$

$$y_t = \gamma \cdot t + u_t + \mu, \quad t = 1, \dots, 156, \tag{3}$$

where Equation (3) defines a simple regression y_t for the deterministic terms (linear trend and a constant) and Equation (5) for deterministic dummies, which are essential to be included due to the COVID-19 crisis. Nevertheless, simple regression in the OLS model is used for the first observation to start checking the level of integration alongside the misspecification tests of autocorrelation, normalities and heteroskedasticity. The sign u_t is a first-order autoregressive process $u_t = \varepsilon_t / (1 - \rho)$. The constant μ is related to the initial value of y_t . Therefore y_0 contains information on the units of measurement so we have $y_0 = \mu + u_0$, and in practice $y_0 \cong \mu$, while error u_0 is very small. Nevertheless, γ measures the growth rate and ρ is a sign of differenced model. Moreover, normalities should follow the time series, with a test for sample size $n \geq 156$ ([Arnastauskaitė et al. 2021](#)). Hence, the differenced VAR(1) model is:

$$\Delta x_t = \alpha \cdot \beta' \cdot x_{t-1} + \mu_0 + \mu_1 \cdot t + \varepsilon_t, \tag{4}$$

where μ_0 is a constant, $\mu_1 \cdot t$ is a trend, all short-run dynamics in matrix Γ_i are zero, long-run matrix is $\Pi = \alpha \cdot \beta'$ and α and β are $p \cdot r$ matrices. In this case ($\Gamma_i = 0$), the cointegrated VAR model is used in this research where the first row reproduces approximately the Π as of $\alpha_{11} \cdot \beta'_1$. Lastly, x_{t-1} is a non-static variable.

Overall, the moving average (MA) model is initialised on a VAR model without short dynamics and the dummies in regression of VAR are:

$$y_t = \varnothing_{tr} \cdot D_{tr,t} + u_t + y_0, \tag{5}$$

where $D_{tr,t}$ is a transitory shock dummy and \varnothing is a number of restrictions.

3.3. Data

The data vector is defined using data for Slovenia and the monthly time series was collected from three different sources. The period reviewed is from 2008 to 2020 for the variables of the twelve most common groups of microbes that caused diseases. The dependent variable is tourist arrivals. Additionally, a dependent variable of greenhouse gas emissions is introduced.

The data sources of variables are the office that collects the data on microbes and diseases, statistical data and GHG data. Therefore, there are two Slovenian offices: the National Institute of Public Health (NIPH) and the Statistical Office of the Republic of Slovenia (SORS). Moreover, the non-profit organisation Global Monitoring Laboratory from Hegyhatsal, Hungary, provides the GHG data. Sample out is determined for the last quarter of 2020 to check the robustness of the model. The sample length is selected depending on the availability of the data in the NIPH data tree. There are 156 observations, and the in-sample is defined from January 2008 to September 2020.

The dependent variable is tourist arrivals collected from SORS (SORS 2022). Due to the lockdown in Slovenia, there were no tourist arrivals in April 2020.

The groups of microbes that cause diseases are isolated from the NIPH and are arranged as: Cholera, Salmonella, Dysentery, *E. coli*, Campylobacter, Enterococcus and Staphylococcus, Botulism, Clostridium and Bacillus cereus, Viruses, Viruses plus COVID_19, Listeria, Sepsis and Hepatitis A. These independent variables data are obtained from NIPH (NIPH 2022).

An additional independent variable data for greenhouse gas emissions is obtained from Global Monitoring Laboratory (GML) (GML 2022).

The abbreviations of the groups of variables used are presented in Table 2.

Table 2. Abbreviations for the variables.

Variable	Abbreviation	Source
Cholera	CH	NIPH
Salmonella	SA	NIPH
Dysentery	DY	NIPH
<i>E. coli</i>	EC	NIPH
Campylobacter	CA	NIPH
Enterococcus and Staphylococcus	ES	NIPH
Botulism	BO	NIPH
Clostridium and Bacillus cereus	CB	NIPH
Viruses	VI	NIPH
Viruses plus COVID_19	19	NIPH
Listeria	LI	NIPH
Sepsis	SE	NIPH
Hepatitis A	HA	NIPH
Greenhouse gas emissions	GHG	GML
Tourist Arrivals	ARR	SORS

Note. NIPH—National Institute of Public Health, GML—Global Monitoring Laboratory, SORS—Statistical Office of the Republic of Slovenia.

While there is no direct and evident consequence of diseases on tourism, the above-mentioned methodology proposed for time series forecasting by Juselius (2009) will be used to check whether there are connections between diseases caused by selected microbes and the evolution of tourist arrivals. The robustness and advantages of the methodology are validated by Escribano et al. (2021). Cross-validation procedures are provided to prospectively assess the performance of our methodology (Lin and Eck 2021).

4. Results

The designed models have shown that the number of tourist arrivals (tourist demand) depends on microbes, which is not so unusual when people decide whether to travel or not based solely on their health status. Economic papers more or less discuss the financial situation of tourists, tourist demand, supply and purchasing power parity but, as can be seen in this paper, society has remarkably forgotten that humans are still dwellers in a habitat. The detailed results are presented below.

First, the ordinary least squares (OLS) method is performed using regression analysis to determine the study’s initial results. Then, the plotting continues and the autoregressive vector model is introduced. At the last point of the investigation, the prediction is presented:

- first, on the in-sample from January 2008 to September 2020 and out-sample from October 2020 to December 2020,
- second, the forecast for the period after the in-sample period, e.g., January 2021 to December 2022.

4.1. Econometric Results

4.1.1. OLS

Observing the data in OLS, the whole sample period covers the practical results, which are in line with theoretical considerations that OLS could give an observation of the data, but not reliable results. The Durbin-Watson statistic, which measures the level of autocorrelation, is 1.47 and indicates the presence of negative autocorrelation. The adjusted coefficient of determination for the model in Equation (6) shows a level of 0.69 of explained variance.

$$\begin{aligned}
 ARR_t = & -50,667.10 \cdot CH_t + 109.73 \cdot SA_t + 451.80 \cdot DY_t + 7848.66 \cdot EC_t + 2144.78 \cdot CA_t \\
 & + 922.03 \cdot EN_t + 38,848.70 \cdot BO_t - 67.58 \cdot CB_t - 44.74 \cdot VI_t - 4.69 \cdot 19_t \\
 & + 12,032.40 \cdot LI_t + 648.87 \cdot SE_t + 3647.38 \cdot HA_t - 460.77 \cdot GHG_t
 \end{aligned} \tag{6}$$

(6.61)^{***}
(7.05)^{***}

(-2.84)^{***}
(-2.71)^{***}

The regression analysis shows that only a few regression coefficients are statistically significant, e.g., ARR_t , EC_t , CA_t , VI_t and 19_t ; therefore, only statistically significant coefficients will be used in further analysis. The t -test statistics are written in parentheses, whereas the 1% significance is indicated by three stars.

4.1.2. Misspecification Tests

The essential procedure consisted in testing the time series data. The results in Table 3 show that all variables are to be treated in natural logarithms (ln). Nevertheless, all variables suffer from serial autocorrelations except, 19_t , therefore, for the ARR_t , EC_t , CA_t , VI_t the first difference is a benchmark solution (x_{t-1}). The Augmented Dickey-Fuller (ADF) test for a unit root test and Lilliefors test for normalities are used for 156 observations.

The summary statistics show that all variables have high volatilities between the minimum and maximum values, whereas the highest volatility is for $\Delta 19_t$. Therefore, the transitory shift dummy is needed, number 1 is set for April and May 2020 and the other months are 0. The zero value of ARR_t in April 2020 (due to lockdown) was set as 1, which is indicated in the minimum range in Table 3. Overall, the normalities in ΔVI_{t-1} , $\Delta 19_t$

and ΔARR_{t-1} could not be found. Nevertheless, the procedure in the following steps (Equation (7)) is vital and the data vector is now set as Equation (1):

$$V = \mathbb{R}^5 : \Delta^{SI} [ARR_t \ EC_t \ CA_t \ VI_t]_{156}^{I(1)} [19_t], T = 1, 2, \dots, T, \tag{7}$$

where *SI* indicates Slovenia.

Table 3. Mis-specification tests and descriptives of summary statistics.

Variable	ADF Test	Diff. ADF	Normality	Mean	Min	Max	New Abb.
EC_t	-1.95	-9.26 ***	0.08 *	15.33	1.00	76.00	$\ln EC_{t-1}$
CA_t	-1.25	-5.99 ***	0.04	92.82	24.00	221.00	$\ln CA_{t-1}$
VI_t	-1.23	-2.47 *	0.13	1328.00	5.00	4478.00	$\ln VI_{t-1}$
19_t	0.03	-3.21 ***	0.20	2132.20	55.00	48,566.00	$\ln 19_t$
ARR_t	-1.81	-7.93 ***	0.35	3.46×10^5	1.00	1.07×10^6	$\ln ARR_{t-1}$

Note. EC_t —*E. coli*, CA_t —Campylobacter, VI_t —Viruses, 19_t —Viruses plus COVID_19, ARR_t —Tourist Arrivals, ADF—Augmented Dickey-Fuller, Diff—differenced variable, abb—abbreviation, *,***—10% and 1% significance level, respectively. Sources: authors compilation based on Table 2.

4.1.3. Plotting and Programming Reference

The next crucial and influential step is plotting the differenced data to become familiar with the dispersion of the data. In Figure 4, the time series shows integrated influence between the variables. We have decided to present different impacts in ΔARR_{t-1} in Appendix A. From the plots, the dispersions of the data confirm previous decisions of the impact of microbes on tourist arrivals. The direction will be studied in the next section using the VAR model.

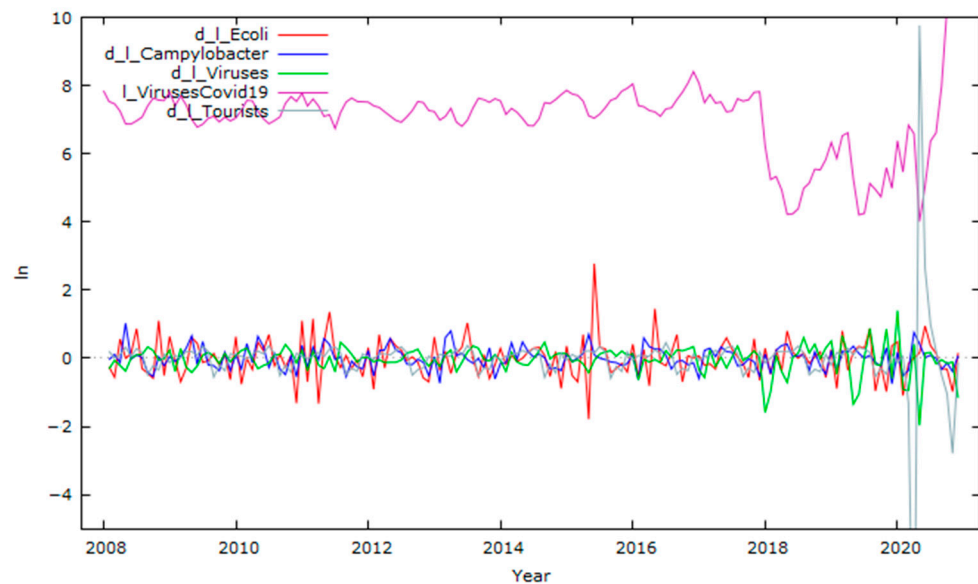


Figure 4. Differenced variables. Sources: authors compilation based on Table 2.

4.1.4. VAR Analysis

The cointegrated VAR analysis is used in this step. The analysis adds some significant results (Equation (8)) and the direction of impact on tourist arrivals as dependent variables in the research. The cointegrated VAR(2) model is:

$$V = \mathbb{R}^5 : \frac{SI}{\Delta} [ARR_t EC_t CA_t VI_t Dtr_t]_{156}^{I(1)} [19_t] = \left\{ \frac{SI}{\Delta} \begin{bmatrix} -0.47^{(-5.74)} & 0.17^{1.17} & 0.63^{2.67} & 2.02^{6.45} & -2.45^{-2.68} \end{bmatrix}_{156}^{I(1)} \begin{bmatrix} -2.12^{-8.39} \end{bmatrix}_{t-1} \right\} + \left\{ \frac{SI}{\Delta} \begin{bmatrix} -0.16^{(-2.20)} & 0.21^{1.48} & 0.53^{2.17} & 0.57^{-2.74} & -2.45^{-2.68} \end{bmatrix}_{156}^{I(1)} \begin{bmatrix} 2.14^{8.39} \end{bmatrix}_{t-2} \right\}, \quad (8)$$

where t -test statistical values are in parentheses and forecasting is seen in Figure 5.

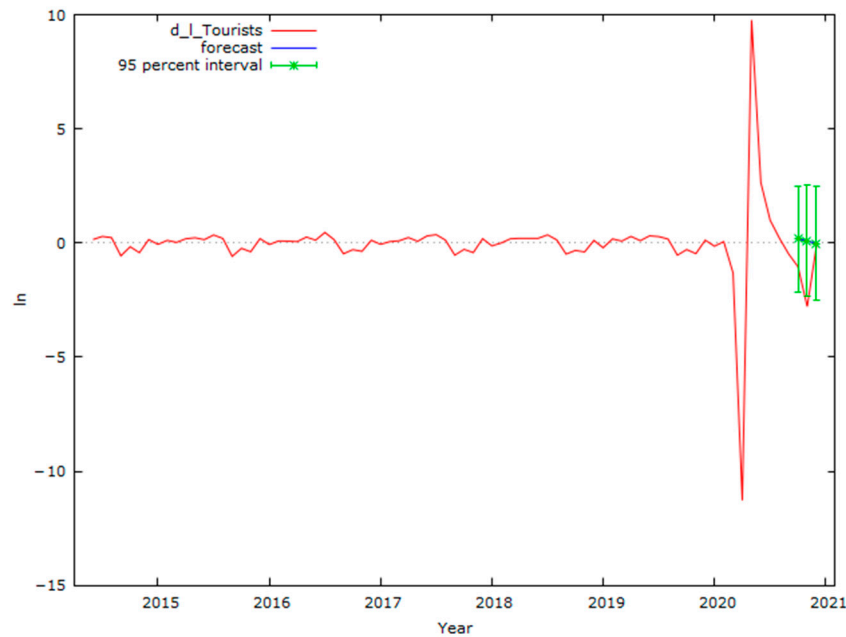


Figure 5. Forecast for tourist arrivals from October 2020 to December 2021. Sources: authors compilation based on Table 2.

The main conclusion is that all independent variables are influential, dependent on the first and even more significantly on the second lag. This is the finding: that the negative impact of viruses will be over after a second lag. Bacterial infections have a positive impact on tourist arrivals. Nevertheless, the viruses positively affect tourist arrivals in the second lag. Therefore, the next forecast is that a massive rise in tourist arrivals could not be expected before the end of 2022 (Figure 6). The models are showing that there will be a significant increase, but a steady state. This finding goes alongside the second lag and therefore the next tourism boom should be expected, if the only concern is microbes as the independent variables, in a two to three-year period. The rise in tourist arrivals would be provided mainly through bacterial infections, whereas COVID-19 has now had a significant positive impact. The reliability of the cointegrated VAR model could be observed in Figure 5, where the in-sample from January 2008 to September 2020 provides a considerable out-sample from October 2020 to December 2020.

The main conclusion is that the VAR model predicts valid results. The sample-in and sample-out are as previously described: first, the process of in-sample from January 2008 to September 2020 and out-sample from October 2020 to December 2020 (Figure 5), and second the forecast for the period after the in-sample period, e.g., January 2021 to December 2022 (Figure 6).

Overall, the VAR model and causality testing confirm uni-causality from ΔEC_{t-1} to ΔARR_{t-1} and ΔCA_{t-1} to ΔARR_{t-1} with D-W statistics of 2.05 and 2.06, respectively. Additionally, there is uni-causality from ΔARR_{t-1} to ΔVI_{t-1} with a low explained variance, while the adjusted deterministic coefficient is at the 11% level. Nevertheless, there is bi-directional causality between $\Delta 19_t$ and ΔARR_{t-1} with a D-W statistic of 2.00 and a deterministic coefficient of 0.82. This results in causality representing the informative direction that has been discussed above in a cointegrated model.

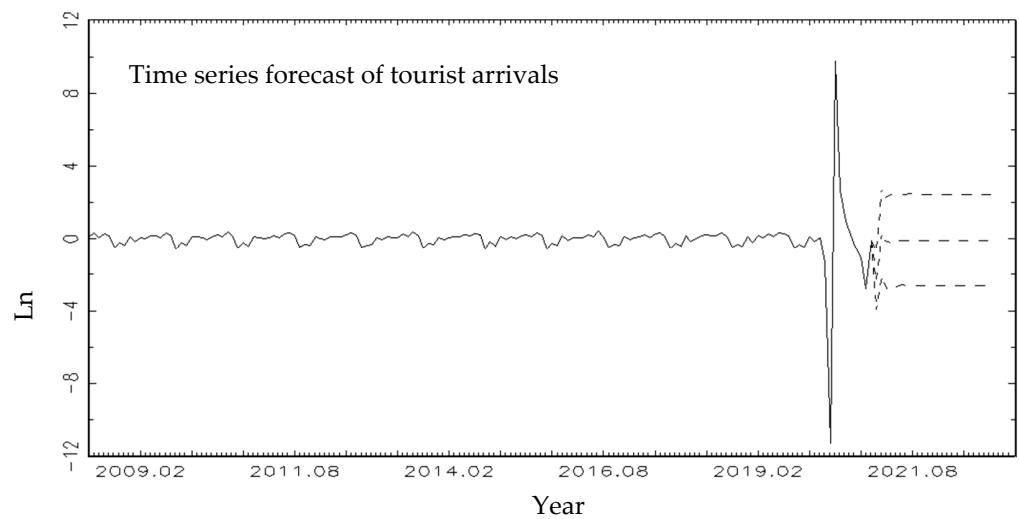


Figure 6. Forecast for tourist arrivals from January 2021 to December 2022. Sources: authors compilation based on Table 2.

5. Discussion

There is less need for extensive ex-post research in tourism during a pandemic. Already an ex-ante study found that microbes will cause tourism demand, but tourism managers and other actors were not satisfied with this and did not believe in it. Moreover, the premium research presented in this article confirms that there is still a severe impact of viruses on tourism demand, but this effect disappears with the second lag, which technically means that, once the pandemic has started, it will disappear in a second lag, as discussed by [Gricar et al. \(2022\)](#). On the other hand, the next pandemic caused by microbes is just around the corner, this time by bacteria. The influential shock will be in a positive direction but quite significant, which means that several tourists will suffer from “poisoning” and infections. Therefore, the study suggests that the medical system should be prepared for such cases, as people could be highly infected during holidays.

On the other hand, few tourists will get infected with viruses, but the figures will still be noteworthy. Tourism managers should establish hotspots for first aid treatment of infected people to provide faster medical treatment. In summary, the economic view is much more stable, while bacterial infections cause a significant increase in tourist arrivals afterwards (e.g., 24 months). This is a result of the scenario-based research on tourist arrivals as a regressed variable as an ex-ante prediction. It is a forecast that can be valuable to raise a warning. This finding could be related to the previous research by [Mazard et al. \(2016\)](#) and [Donohoe et al. \(2015\)](#) that microbes have a big impact on infectious diseases. Additionally, [Kolokotsa et al. \(2021\)](#) researched the relation between bacteria and tourist flows using antibiotics as a research variable. For example, *E. coli* and tourism causality were researched by [Goldberg et al. \(2007\)](#) and published as a case study by [Honda et al. \(2019\)](#). For *Campylobacter*, there were already reported cases in the tourism industry, as in [Kampmann et al. \(2016\)](#).

The main discussion of the results of the study focuses on:

1. the research problem in terms of its technical and intuitive components—a plan of action, or research design, which will allow answering the question,
2. the correct specification of variables should be determined using consistent theory,
3. the use of an advanced modelling procedure with a state-of-the-art methodology,
4. ex-ante research and forecasting that are essential for a successful prediction and are essential in a successful business planning,
5. to make the data manageable, it must be segmented,
6. the study confirms that people continue to interact with the environment in which they live. Economists have been hiding this fact from their research, but by combining these definitions with econometrics, we can see how they fit together in tourism:

- a. bacteria and other microbes have a significant impact on human health and tourism should anticipate that impact in advance. Forecasting tourism demand using time series analysis will help prepare companies for the coming year(s),
- b. human health influencers include significant variables: viruses, *E. coli*, and *Campylobacter*—including strains that cause stomach flu, diarrhoea and food poisoning—which have the potential to increase tourism demand,
- c. on the other hand, ex-ante research conducted before the COVID-19 pandemic found that a decline in tourism demand caused by at that time unnamed viruses is an example of justified ex-ante forecasting,
- d. short-term and medium-term causalities are:
 - from *E. coli* and *Campylobacter* to tourist arrivals,
 - from tourist arrivals to viruses (spreading of diseases),
 - bi-causality from COVID-19 to tourist arrivals. This is a sign that the pandemic is not over yet (e.g., end of 2022), and supports the definition of the pandemic by [Gricar et al. \(2022\)](#).

There are some limitations of the study. It did not include all the variables studied in the VAR model, but only the significant ones provided by OLS, e.g., *E. coli*, *Campylobacter*, viruses and viruses plus Covis-19. The subsequent delimitation is time; there are data until the end of 2020, but the year 2021 is therefore still omitted. The last delimitation is country-specific research, while broader results from the European Union could have been obtained using panel data methodology. Nevertheless, the robustness of the data and modelling was confirmed by a country where monthly data is publicly available, which adds value to the research.

6. Conclusions

First, the previously presented results on unprecedented events were summarised. Second, the robustness of the prediction using time series was validated by a new, more extended empirical test. Finally, the modelling process was checked against various factors such as events and ex-ante forecasts. The implications of this study are crucial for national policy directions, management and marketing companies' decisions.

The empirical results show a tourism boom in the following years. Several determinants influence tourist arrivals. Importantly, two variables on bacteria have a positive significant result that could affect the tourism arrivals variable. The information is a landmark for decision-makers. Nevertheless, implications are broader and the most important is strategic management based on quantitative decisions and forecasting for future, usually named, unpredicted events. In this case knowledge, experiences, and science come into one integrated community for better forecasting and management in tourism. Ex-ante definitions can be crucial to maximising scientific results and business revenues.

The panel data and panel cointegration could be an amicable solution and benchmark for future research. Overall, for future research, all variables could be treated in a misspecification test to check whether some provide additional explanatory results, primarily on greenhouse gas emissions.

However, the limited time series research is an intuition regarding the chosen variables. There is no strict methodology for how to extract time series. The main contribution consists of a clearly defined research hypothesis. In addition, this could also be a future direction for similar research to contribute to well-defined research problems or shocks. Overall, the paper outlines the importance of ex-ante research.

The study has policy relevance in showing how time series data can be used in predicting. Moreover, the power of the study's predictions shows that decisions, could be improved by knowing predictions and being prepared for them. Ex-ante research and forecasting can be essential parts of successful business.

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Informed Consent Statement: Patient consent was waived due to research on the secondary data obtained by the National Institute of Public Health.

Data Availability Statement: The data are in the public domain and therefore available on public websites.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

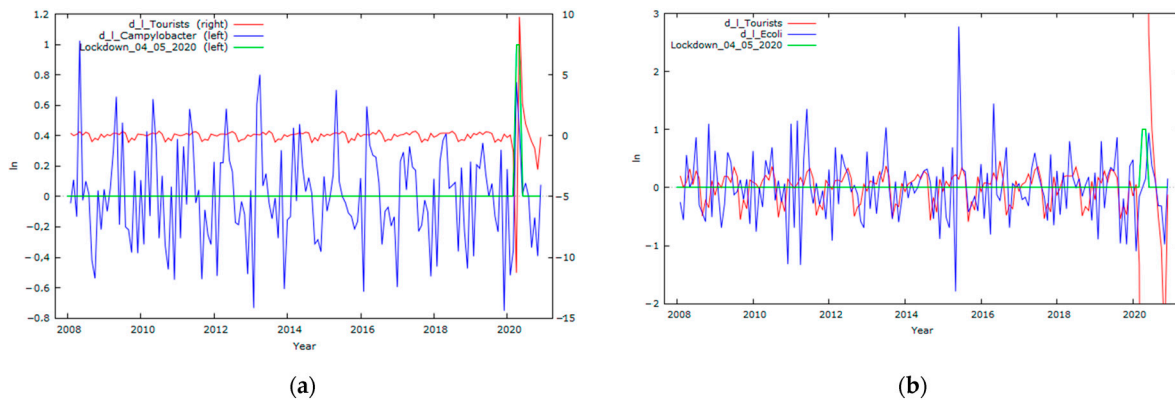


Figure A1. Dispersion of data for time series. (a) Between the ΔARR_{t-1} and ΔCA_{t-1} ; (b) Between the ΔARR_{t-1} and ΔEC_{t-1} .

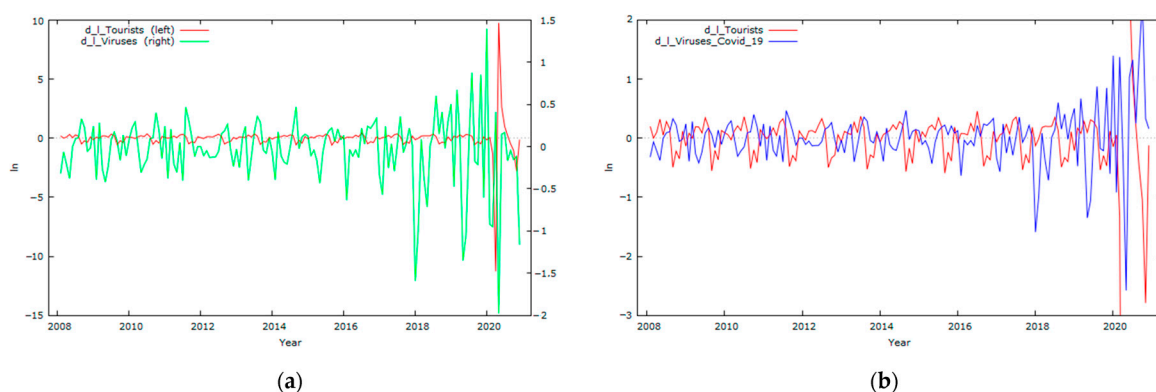


Figure A2. Dispersion of data for time series. (a) Between the ΔARR_{t-1} and ΔVI_{t-1} ; (b) Between the ΔARR_{t-1} and $\Delta 19_t$.

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